Application of Frame Energy Based DCT Moments for the Damage Diagnosis in Steel Plates Using FLNN

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Abstract: *This paper discusses the application of frame energy based Discrete Cosine Transformation (DCT) moment features for the detection of damages in steel plates. A simple experimental model is devised to suspend the steel plates in a free-free condition. Experimental modal analysis methods are analyzed and protocols are formed to capture vibration signals from the steel plate using accelerometers when subjected to external impulse. Algorithms based on frame energy based DCT moment feature extraction are developed and prominent features are extracted. A Functional Link Neural Network (FLNN) is modeled to classify the condition of the steel plate. The output of the network model is validated using Falhman testing criterion and the results are compared.*

Keyword: *Experimental Modal Analysis, Frame energy, Discrete Cosine Transformation, DCT moments, Falhman criterion, Structural Health Monitoring. Functional Link Neural Network.*

I. INTRODUCTION

Damage can be defined as the changes introduced into a system that brings adverse effects in the present and future performance. Damage becomes expressive when it is compared between two different states of the system. Cracks are well-defined as any unintentional discontinuities in the shaft material. The occurrence of the faults or damages in the structures is quite unavoidable mainly due to environmental conditions, improper handling, poor maintenance and wear and tear. A detailed comprehensive survey on the nondestructive measuring techniques has been dealt by Brinksmeier [1]. Dimarogonas [2] presented a detailed review on nondestructive testing to detect and monitor cracks in beams, plates, rotors, and turbine plates. An extensive literature review of the state of art vibration analysis and damage detection has been published by S.W. Doebling [3]. A detailed survey of the state of art in the damage detection field using modal analysis has been presented by Richardson [4]. A detailed review of the different vibration and acoustic methods such as the time and frequency domains, acoustic emission techniques are presented by Tandon and Nakra [5]. Using fracture mechanics method, Dimarogonas [2] and Anifactis [6] computed the equivalent stiffness and developed a model for crack detection in beams. An experimental technique to estimate the location and depth of a crack in a beam has been developed by Adams and Cawley [7]. The methodology of crack detection based on natural frequency changes has been closely studied by Shen and Pierre [8].

The nondestructive approach is engaged towards the identification of the damages in the steel plate. Non Destructive Testing (NDT) can be defined as the study of the impulse response of a system due to an external excitation that confronts the dynamic nature of the system under test. The vibration signal is recorded from the system when it is subjected to an external excitation. The presence of damage in the system is studied by closely studying the vibration pattern at an instance. The vibration pattern carries the dynamic characteristics of the system such as fundamental frequency, damping ratio and mode shape.

In this paper, the exponential decay of the vibration signal captured from the accelerometers when the steel plates are subjected to an external impulse are studied. The dominant features from the vibration signals are extracted and a neural classifier is modeled to classify the condition of the steel plate.

II. METHODOLOGY

Experimental Modal Analysis (EMA) is defined as a process of acquiring acceleration response data (excitation of the structure using external force and obtaining the response to the force) and identification of the modal parameters [9]. A cold rolled steel plate of size 60 cm width and 24 cm length and of thickness 2mm and mass 1.2 kg is considered for this study. To suspend the steel plate in a simply support boundary condition an aluminium framework is fabricated. The steel plate is suspended over the framework using two thin threads as shown in the Figure 1.

Using EMA, the vibration study can be performed in x, y and z planes Since the steel plate is an isotope, the characteristics of the vibration response in all three planes is similar, Hence the experimental design is developed to study the vibration response of the steel plate in x-y plane.

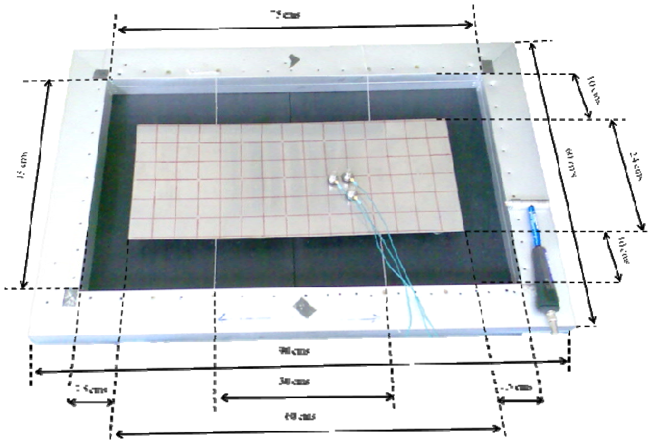

Figure 1: Steel plate suspended using two thin threads

Roving hammer test

In this roving hammer testing procedure, the structure under test is mounted on the experimental setup. The accelerometers locations are evenly distributed over the structure. An impulse signal is generated on the structure by striking the impact hammer at different locations and observing the vibration acceleration pattern at different locations. The location of strike of the impact hammer is randomly selected. The number of accelerometers used in this test depends on the dimensions of the structure and the location of interest. Figure 2 depicts the roving hammer test where the location of the impact hammer is changed during every test while the accelerometers are placed intact in the numbered locations

Roving accelerometer test

The roving accelerometer test is similar to the roving hammer test. In this test the structure under test is mounted on the experimental setup and the location of strike of the impact hammer is fixed. The accelerometers are placed at even locations on the structure. The location of excitation is fixed at the same place throughout the test, while the accelerometer locations are changed during every trial of the test. The accelerometer roving test is shown in Figure 3.

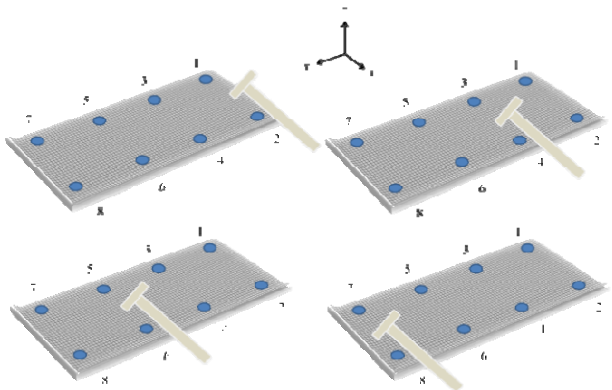

Figure 2: Roving hammer test

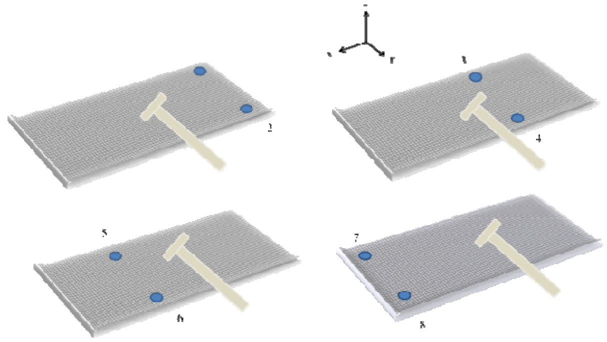

Figure 3: Roving accelerometer test

Materials and Protocol Design

The data collection protocol is the set of methods or rules framed to ensure the consistency of the measured vibration signals throughout the data collection process. The steel plate is divided into 6 rows and 15 columns. The area of the cell is 4 cm^2 and the cells are numbered sequentially from 1 to 36. An experimental protocol is designed based on both the roving hammer and roving accelerometer tests. The accelerometers are mounted over the corners of the cells based on the protocol design shown in Figure 4.

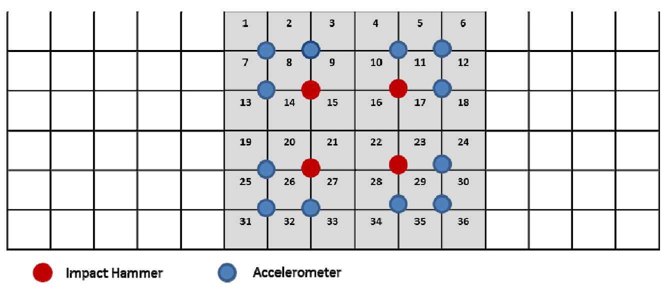

Figure 4: Experimental protocol design

An impulse is generated when the impact hammer strikes over the location on the steel plate. The accelerometers capture the vibration signal connected to the Data Acquisition System (DAQ). The experiment is carried out on all the 36 cells and 144 possible combinations of the 4 protocols by changing the positions of the accelerometers and the impact hammer. The recorded signals are sequentially numbered and saved.

Small micro damages of size 531 μm to 1870 μm are created throughout the steel plate inside the 36 cells and the data collection is carried out for all the locations. The experimental data is collected at various locations of the steel plate under normal and fault conditions. The experiment is repeated and the vibration signal is obtained from 10 steel plates of similar dimensions. Thus 1440 samples are captured and recorded for normal conditions. Similarly 1440 samples for fault conditions are collected after drilling small holes on the steel plates. The data collected is stored in the native 'XLF' file format supported by the DAQ. The files are later converted into 'WAV' file format for further processing through MATLAB.

Feature Extraction

The vibration signals are captured using an experimental protocol from the steel plate at a sampling rate of 4 kHz [10]. The vibration signal is recorded for 20 seconds during the impact test. The time t_p corresponding to the first peak magnitude v_p is identified and the signal recorded from $(t_p - 0.5)$ seconds to $(t_p + 14.5)$ seconds is trimmed for 15 seconds to maintain uniformity throughout the analysis. The trimmed signal is then segmented into definitive frames of size 1024. The representation of the blocked frames is shown in Figure 5.

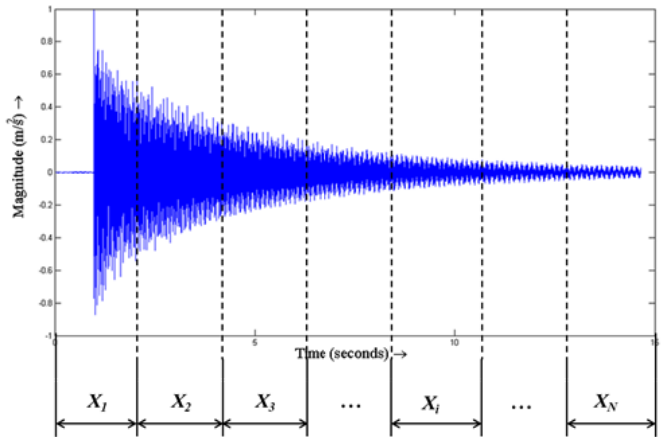

Figure 5: Vibration signal blocked into frames

Frame Energy

The total energy of a signal is defined as the sum of the squared magnitudes of the signal components. The law of conservation of energy states that, the energy can neither be created nor be destroyed, but can be transformed from one form to another. This law applies to this problem domain, where the energy in the form of mechanical force exerted by the impulse hammer is distributed all over the steel plate as vibration pattern. The energy in the form of vibration is affected by the damages present in the steel plate. The energy of the frame is calculated by computing the sum of the squared magnitudes of each frame. The Energy $\boldsymbol{E}$ of the signal is given in equation (1)

$$\boldsymbol{E} = [e_1, e_2, e_3, \ldots, e_i, \ldots, e_N] \quad (1)$$

where e_i is the frame energy in the i^{th} frame and it is represented in equation (2).

$$e_i = \sum_{j=1}^{1024} x_{ij}^2 \qquad (2)$$

where x_{ij} is the j^{th} signal of the i^{th} frame. Typical frame energy of a normal and faulty signal is shown in Figure 6.

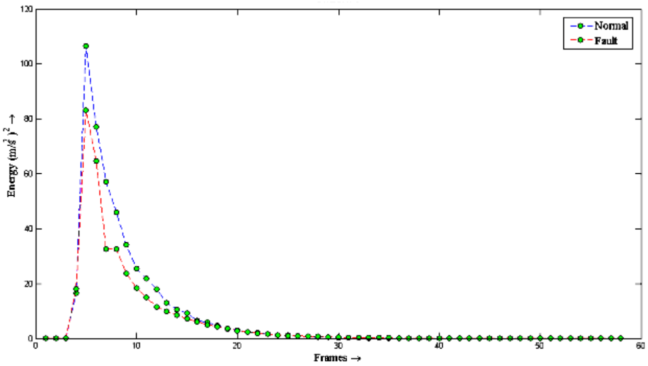

Figure 6: Typical Frame energy of normal and fault signals

DCT Moments

Discrete Cosine Transformation is applied over the computed frame energy. A bouncing ball shaped DCT moments are obtained as seen in Figure 7. Algorithms are developed to extract the first 4 DCT moment coefficients.

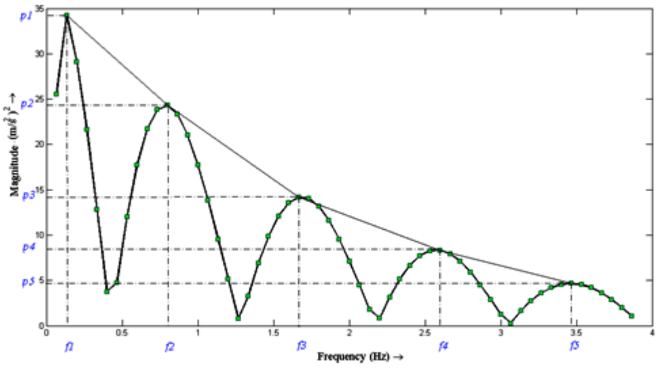

Figure 7: A typical representation of DCT peak moments

Classification

Artificial Neural Networks are widely used for pattern classification. In this research work, a Functional Link Neural Network Classifier is modeled to classify the condition of the steel plate. The features extracted from the vibration signal are provided as input and the condition of the steel plate as output to the neural network.

The features extracted from three accelerometer channels constitute a feature sample. The features are extracted from the steel plates in both the normal and fault conditions. The database consists of 2880 samples (1440 normal and 1440 fault samples).

The extracted features are further processed to remove outliers. The features are labeled and then associated with condition of the steel plate. The dataset is normalized and the principal components are identified and the data dimensionality is reduced.

In the original dataset, the columns 1,2,3,4 contain the DCT moment information of Accelerometer 1, columns 5,6,7,8 contain the DCT moments of Accelerometer 2 and columns 9,10,11,12 contain the DCT moments of the Accelerometer 3.

The Functional Link Neural Network (FLNN) has functional inputs which are the expansion of the original input along with the functional links. Such that, the input neurons $x_1, x_2, x_3, \ldots, x_n$ where n=12 is manipulated with the n-1 input neurons to obtain a functional composition of x_1x_2, x_2x_3, x_3x_4, x_4x_5, … , $x_{n-1}x_n$.[11]. The database finally contains (n + n-1) features which are 21 input neurons and 1 output neuron.

Training: The processed features contain the input – output association. The network model contains three layers namely input, hidden and output. The input layer is provided with the feature vectors which constitutes the input neurons to the network. The output layer is associated with the target vectors corresponding to the input vectors. The hidden neurons in the hidden layer are allocated experimentally. The hidden neurons contribute towards the weighted connections of the neural network. The 'trainlm' function available in MATLAB neural network toolbox is used to model, train and simulate the neural network. The dataset is divided into training samples of 60%, 70% and 80% samples.

Testing: The trained network model is tested and validated against the remaining testing samples which include unseen inputs by the trained network. The network is tested with normal method and the 'threshold and margin criterion' proposed by Falhman [12]. In this method the output classes: class1 and class2 are associated to 0.1 and 0.9 respectively. The threshold value is set in such a way that, the output values of the simulated network lying between 0 to 0.35 is considered as 0.1 (class1) and output values lying between 0.65 to 0.9 is considered to be 0.9 (class2). The target output values above 0.35 and below 0.65 are considered 'marginal' and are not considered as correct during training. The neural network training results are testing using this method and are tabulated.

III. RESULTS AND DISCUSSION

The training parameters of the FLNN model are explained as shown in Table 1. The FLNN model is trained and the results are validated in both normal method and Falhman method. The results of the trained network: mean classification accuracy, mean sensitivity, mean specificity and mean epochs are tabulated in Table 2.

Table 1: FLNN Training Parameters

Input Samples:	21
Hidden Neurons:	20
Output Neurons:	1
Training Tolerance:	0.01
Testing Tolerance:	0.1
Learning Rate:	0.01
Hidden Activation Function:	logsig
Output Activation Function:	tansig

Table 2: FLNN Training Results

	Normal Testing			**Falhman Testing**		
	60%	**70%**	**80%**	**60%**	**70%**	**80%**
Mean Classification Accuracy	95.89	96.16	97.00	96.19	97.07	98.53
Mean Sensitivity	88.66	91.01	93.00	92.15	93.11	94.15
Mean Specificity	87.00	88.96	89.98	92.17	93.82	94.16

The results show that 80 percent data samples produce better results compared to 60 percent and 70 percent samples. Though the larger the number of samples, the more the complexity and weighted connections of the network.

IV. CONCLUSION

In this work, an experimental framework was developed based on the non-destructive testing and experimental modal analysis to hold the steel plate. A simple protocol based on the roving hammer and roving accelerometer tests were designed to perform impact testing and capture the vibration signal from the steel structure. Frame Energy based DCT Moment features were extracted using algorithms from the vibration signals. Data preparation methods were developed to formulate the feature vectors for classifier models. Functional Link Neural Network was modeled to classify the condition of the steel structure. The results of the network model were validated against the Falhman criterion and the results with the conventional network model were compared.

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